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An Experimental Study on the Analysis of Gait Disorders Through Multimodal Feature Extraction

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Abstract. Accurate detection of gait abnormalities is essential for the diagnosis and monitoring of neuromotor disorders. This work presents the experimental design for the multimodal acquisition and extraction of temporal, spatial, and frequency-domain features in patients with motor impairments, using accelerometers and an RGB-D camera (Kinect). The clinical protocol, sensor configuration, and controlled environment are described to achieve more accurate data collection of patients' gait. Additionally, signal processing techniques are detailed to extract relevant biomechanical variables along with their clinical justification. Preliminary results with healthy subjects and the support of specialists validate the system's accuracy and reproducibility. Clinical implications, limitations, and future directions focused on integrating machine learning for gait pathology classification are discussed. This study lays the groundwork for developing objective and non-invasive tools to enhance the assessment and rehabilitation of patients with movement disorders.

Keywords: Gait Pathology, Clinical Study, Feature Extraction.

1 Introduction

Human gait is one of the most complex motor functions of the body, and its analysis provides valuable information about neuromuscular integrity and an individual's functional status. Gait pattern abnormalities are common clinical signs in diseases such as Parkinson's, multiple sclerosis, stroke, and other neurological and musculoskeletal conditions. Early and accurate detection of these abnormalities is key to planning timely and personalized therapeutic interventions [14].

Clinical gait analysis has been performed through qualitative observation or using high-cost laboratory equipment such as optical motion capture systems or force platforms. However, advances in wearable technologies have promoted the use of inertial sensors and depth cameras as accessible and effective alternatives for collecting kinematic and dynamic data in real-world or clinically adapted environments [11, 12]. In particular, the combination of triaxial accelerometers and RGB-D cameras, such as the Kinect sensor, enables multimodal motion capture by integrating temporal, spatial, and frequency-domain information with a high level of resolution.

However, the clinical quality and usefulness of the collected data largely depend on the experimental design used. Factors such as sensor placement, environmental conditions, movement protocol, and subject characteristics can introduce significant variability if not properly controlled. Therefore, it is essential to establish a standardized experimental environment that ensures data consistency, validity, and reproducibility, facilitating subsequent quantitative analysis and the training of automated classification models [17].

This work aims to develop a *clinically oriented experimental design* for the extraction of multimodal gait features in patients with and without pathologies, using accelerometers and RGB-D cameras. The methodology is based on the *Biodesign* approach [20], which structures the process into three phases: identification of the clinical need, invention of the technological solution, and planning for its implementation. This perspective ensures that the experiment not only meets scientific and technical criteria, also addresses a real need within the clinical setting, and aligns with ethical and regulatory standards such as those established by the Good Clinical Practice (GCP) guidelines and the IEEE 11073 family of standards.

2 Theoretical Framework

Gait analysis is a multidisciplinary field that involves principles from biomechanics, biomedical engineering, neurology, and physical therapy. Its main objective is to quantify the kinematic and dynamic parameters of human movement, which allows for the identification of abnormalities associated with various neuromuscular or musculoskeletal pathologies.

2.1 Key Parameters in Gait Analysis

Gait studies focus on three types of features:

-Temporal features: such as step time, stance time, and gait cycle duration.

-Spatial features: such as step length, foot clearance, and stride symmetry.

-Frequency-domain features: obtained through spectral analysis of movement signals, useful for detecting tremors or rigidity, including features such as dominant frequency, spectral energy, spectral entropy, harmonic ratio, and bandwidth, which provide valuable insights into gait regularity, symmetry, and motor impairments.

These parameters can be combined to accurately characterize normal or pathological gait, and are extracted using various instrumental and computational methodologies.

2.2 Traditional Methodologies

Historically, gait analysis was conducted in biomechanics laboratories using instruments such as:

- **Optical motion capture systems.** such as Vicon or OptiTrack, which use multiple infrared cameras and reflective markers to obtain three-dimensional coordinates of body segments [1].
- **Force platforms.** which record ground reaction forces to estimate joint moments and centers of pressure [15].
- **Electromyography (EMG).** to analyze the electrical activity of muscles during gait [10].

Although various techniques for accessing gait parameters have been developed, the mentioned methods present limitations in terms of mobility, cost, the need for calibration, and the involvement of specialized technical personnel.

2.3 Multimodal Analysis and Artificial Intelligence

The integration of inertial sensors (IMUs), which combine accelerometers, gyroscopes, and magnetometers, has gained popularity due to their portability, low cost, and suitability for both clinical and home environments. These devices enable trajectory reconstruction, angular velocity estimation, and detection of gait pattern variations, using signal processing techniques like Kalman filtering and gait cycle segmentation. Concurrently, RGB-D cameras such as Microsoft Kinect provide markerless, three-dimensional motion capture by combining RGB images with depth data, facilitating real-time skeleton tracking despite limitations in lateral accuracy and occlusions. Recently, multimodal approaches that fuse data from IMUs and RGB-D systems have proven effective in providing a richer representation of human movement, enhancing the performance of machine learning and deep learning models for gait classification. Additionally, the use of frequency-domain analysis through Fourier or wavelet transforms enables the identification of rhythmic components relevant to motor disorders.

2.4 Biodesign-Based Methodology

As the conceptual basis for this project, the approach proposed in the *Biodesign* book is adopted [20], which guides the development of medical technology solutions through a structured sequence: identification of the clinical need, invention of a feasible solution, and preparation for effective implementation. This methodological framework ensures that the experimental design is not only technically sound but also clinically relevant and aligned with ethical regulations.

3 Methodology

3.1 Experimental Design

The present study has a cross-sectional and controlled experimental design, with an observational clinical component, aimed at characterizing pathological gait through the multimodal extraction of temporal, spatial, and frequency features. The approach combines inertial technologies and computer vision to obtain quantifiable and reproducible data from patients with gait abnormalities.

This design is based on the methodological approach proposed by the book Biodesign: The Process of Innovating Medical Technologies [20], which establishes a systematic framework to identify clinical needs, design technological solutions, validate their functionality, and generate scientific evidence. In this context, gait analysis and capture are considered a relevant clinical need to improve diagnosis and monitoring of patients with neuromotor impairments.

The central hypothesis of the study is that the combination of inertial sensors and RGB-D vision improves the accuracy and sensitivity in detecting abnormal gait patterns compared to single-channel methodologies.

3.2 Population and Sample

The target population consists of adults over 18 years old with a clinical diagnosis of a pathology affecting gait, such as Parkinson's disease, hemiparesis, osteoarthritis, as well as healthy subjects serving as the control group.

Inclusion Criteria. The inclusion criteria for the gait feature extraction experiment ensure that participants adequately represent the target population, can safely perform the tests, and generate valid data. The study includes individuals with a medical diagnosis of gait-related pathologies (such as Parkinson's disease, hemiparesis, or osteoarthritis) and healthy subjects as the control group, aged between 18 and 80 years. Additionally, participants must be able to walk without mechanical assistance to ensure uniformity in data capture and protocol application.

Exclusion Criteria. Exclusion criteria are established to maintain data validity, safety, and integrity during the experiment. Participants with acute injuries or disabling pain on the test day, cognitive impairments affecting comprehension, or the use of orthopedic devices that interfere with sensor placement will be excluded. These measures ensure a controlled and reliable experimental environment.

Study Groups. The study will include a control group of healthy individuals without neuromuscular or musculoskeletal gait impairments and an experimental group of patients with clinically diagnosed gait-altering pathologies. The experimental group will encompass various conditions such as Parkinson's disease, post-stroke hemiparesis, multiple sclerosis, and osteoarthritis. Each participant's specific diagnosis will be documented to allow for stratified analyses, ensuring a representative range of gait impairments for developing robust and generalizable analytical tools.

Sample Size. The sample size in gait analysis studies depends on factors such as the study objective, population variability, significance level (typically 0.05), statistical power, usually 80%, and expected effect size. Resource availability also influences the number of participants. Exploratory studies often use smaller samples (10–30 per group), while confirmatory studies require formal power analyses to ensure valid results. Based on prior research, a minimum of 15 subjects per group is estimated for this study [7, 16].

3.3 Devices and Setup

The combination of triaxial accelerometers and RGB-D cameras is essential for the accurate and comprehensive extraction of kinematic, dynamic, and frequency-based features during human gait. Accelerometers enable direct and continuous capture of localized movements of specific body segments, providing detailed data on linear acceleration, oscillation patterns, and rhythmic variations that are difficult to record through visual methods. Meanwhile, the RGB-D camera offers a global three-dimensional view of the moving body, allowing for virtual skeletal reconstruction and the calculation of spatial parameters such as step length, gait symmetry, and posture. This multimodal capture integrates complementary local and global information into a single analysis, enhancing the accuracy of anomaly detection and reducing the risk of errors caused by occlusions, noise, or artifacts present in a single modality. Therefore, the combined use of these technologies significantly improves data quality and strengthens the validity of biomechanical analysis, particularly in clinical settings where high sensitivity is required for the early detection of gait impairments.

Two types of technologies will be used for data capture in this experiment:

Triaxial accelerometer. IMU sensor with recording on all three axes (X, Y, Z), a sampling frequency of 100 Hz or higher, and a minimum resolution of 16 bits.

RGB-D Camera. Microsoft Kinect v2 with RGB image stream at 30 fps and depth map, enabling real-time human skeleton reconstruction.

3.4 Sensor Positioning

Inertial sensing system for gait parameter recording. Inertial sensing systems are advanced technologies used to accurately capture and analyze gait parameters and other human movements. These systems rely on sensors that measure linear acceleration and angular velocity of body segments. A typical inertial system architecture includes multiple sensors strategically placed on the body, connected to a central processing unit that records and processes the data. Inertial sensors are small and lightweight, enabling comfortable and unrestricted data acquisition during walking. These systems provide precise measurements of kinematic parameters such as joint angles and movement trajectories, as well as temporal parameters like cadence, step length, and stance and swing times. This capability makes inertial sensors versatile tools both in clinical settings for the assessment of musculoskeletal disorders and in sports applications for performance analysis and functional biomechanics [12].

The optimal placement of inertial sensors for gait parameter recording depends on the biomechanical factors of human walking and joint motion, which affect the accuracy and reliability of the collected data. It is generally recommended to mount the sensors on body segments that undergo significant movement during gait, such as the thighs, shanks, and feet (Fig. 1) . For example, placing sensors in the lumbar region or on the legs allows for more direct capture of relevant joint angles and motion patterns. Furthermore, precise placement on specific anatomical landmarks, such as the anterior superior iliac spine for the pelvis or the center of the knee for knee joint flexion, ensures more accurate measurements of kinematic parameters. This strategy not only facilitates a detailed assessment of gait biomechanics but also minimizes the risk of external interferences and motion artifacts, thus ensuring the quality of data obtained for clinical analysis and sports applications [2].

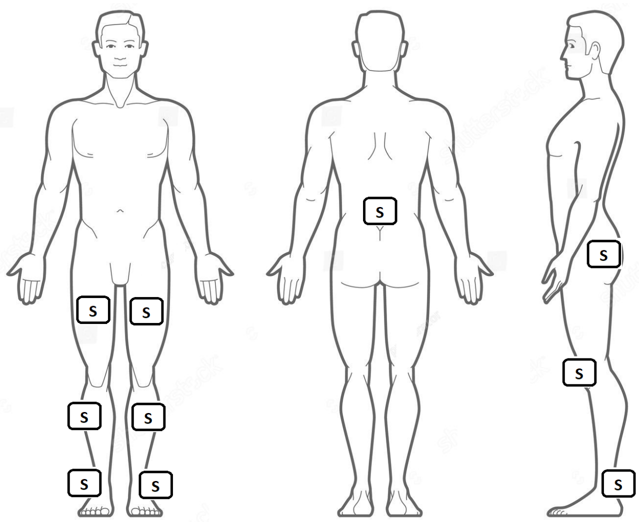

Fig. 1. Sensor positioning.

Vision system with depth camera for gait parameter recording. The use of RGB-D depth cameras, such as the Microsoft Kinect system, has revolutionized gait analysis by providing three-dimensional data capture that combines RGB sensors with depth sensors. This technology stands out for its ease of use, low invasiveness, and cost-effectiveness, making it accessible in both clinical and research settings. Depth cameras allow precise evaluation of kinematic and kinetic parameters without the need for body-attached markers, thereby improving subject comfort. Their application in biomechanical research and rehabilitation has been extensively documented, highlighting their advantages and limitations compared to traditional motion capture systems. Although challenges such as limited accuracy and dependence on lighting conditions exist, depth cameras offer a valuable tool for detailed and accessible analysis of human gait [19].

Proper placement of the capture system is crucial to obtain accurate and reliable data in gait analysis. The location and angle of the camera determine the quality and precision of the measured kinematic and kinetic parameter information. To achieve optimal movement capture, the camera should be positioned at an appropriate height and distance from the subject, generally at waist level and approximately 2 to 3 meters away (Fig.2). This positioning ensures that the subject's entire body is within the camera's field of view throughout the complete gait cycle. Additionally, it is important to adjust the camera's tilt angle to maximize the visibility of body segments and minimize marker occlusion, as shown in Table 1 [8].

Table 1. Technical and configuration parameters for the RGB-D Kinect v2 camera.

Parameter	**Recommended Specification**
Camera model	Kinect v2 (Microsoft) with RGB-D sensor
Depth resolution	512 × 424 pixels
Color resolution (RGB)	1920 × 1080 pixels
Sampling frequency (fps)	30 frames per second (synchronized with IMU signals at 100 Hz)
Distance to subject	2.5 meters for full-body tracking
Mounting height	Approximately 1.0 to 1.2 meters from the ground (waist or hip level of the subject)
Tilt angle	Adjusted to maximize visibility of lower limbs - 45°
Camera placement	Frontal to the subject along the walking path - centered or slightly lateral position
Lighting conditions	Uniform lighting, avoiding strong shadows or backlighting. Direct sunlight should be avoided.
Walking surface	Flat, non-slip surface at least 5 meters long
Recording duration per participant	Approximately 10 minutes - includes 3 repetitions per task
Synchronization with IMU	Using shared visual and auditory events

The synchronization of the collected data will be carried out using shared visual/audio events to align signals. The software will integrate both sources for subsequent analysis.

3.5 Capture Protocol

The tests will be conducted in a controlled clinical environment: Non-slip flat surface of at least 5 meters, uniform lighting, obstacle-free space (with no inclines, declines, or floor level changes).

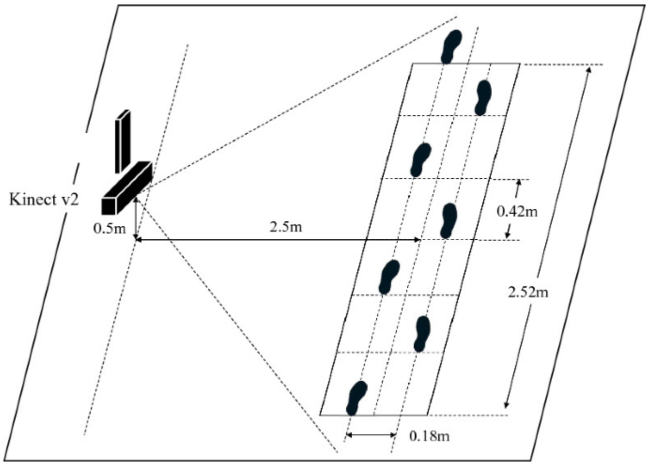

Fig. 2. Camera Placement.

The activities considered are: straight-line walking over 5 meters -back and forth-,180° turn, voluntary pause during the walk, three repetitions per task. The total duration per participant was 15 minutes.

4 Signal Processing and Feature Extraction

4.1 Signal Preprocessing

The signals captured by inertial sensors (IMUs) and the RGB-D camera require a cleaning and synchronization process before extracting relevant features. The general processing workflow includes:

Noise filtering. A fourth-order low-pass Butterworth filter with a cutoff frequency between 5 and 20 Hz is used to eliminate high-frequency noise while preserving relevant movement components [6].

Normalization. Z-score normalization is applied to standardize signals from different participants, minimizing variations due to anatomical or strength differences.

Gait cycle segmentation. Algorithms based on peak analysis of vertical acceleration and events of initial contact (heel-strike) and toe-off are employed, validated by visual references obtained from the 3D skeleton captured by the RGB-D camera [16].

Multimodal synchronization. Temporal alignment of information from the IMU and RGB-D camera is performed using common event signals (acoustic and visual markers) to ensure precise correspondence between data.

4.2 Spatial Features

Spatial variables are fundamental for the functional assessment of gait. In this study, the following spatial variables will be extracted.

Step length is defined as the distance between successive contacts of the same foot. It is a sensitive indicator in motor disorders and pathologies such as Parkinson's disease or hemiparesis.

Step width corresponds to the lateral separation between the feet during gait. An abnormal step width may indicate balance problems or neurological impairment.

Finally, foot clearance height is derived from the vertical component of the 3D skeleton. Reductions in this variable may indicate foot drag or muscle weakness [3].

These features are extracted from the analysis of the skeleton reconstructed by the RGB-D camera, applying basic geometry between joint positions such as the hip, knee, or ankle, as shown in Table 2.

4.3 Temporal Features

Temporal variables are mainly derived from inertial data. These include the duration of the gait cycle, defined as the time between two consecutive contact events of the same foot; the duration of the stance and swing phases, which represent the time each foot remains in contact with the ground or in the air; and cadence, which is the number of steps taken per minute. These variables help differentiate typical pathological gait patterns, such as a prolonged double support phase, which is characteristic in patients with postural instability or motor impairment(Table 2 [9]).

4.4 Frequency Features

A frequency-domain analysis is conducted using the Fast Fourier Transform (FFT) and spectral analysis. The main variables extracted include the dominant frequency, which corresponds to the spectral component with the highest energy; the harmonic spectrum, defined as the ratio between the fundamental energy and the higher harmonics; and spectral entropy, which quantifies the energy dispersion(Table 2 [13]).

This type of analysis is particularly valuable for distinguishing between regular movement patterns—such as those exhibited by healthy subjects—and irregular or asynchronous patterns typically found in patients with neurological conditions.

4.5 Technical and Clinical Justification

From a clinical perspective, these features allow for the quantification of motor impairment, the evaluation of asymmetries, and the identification of fall risks.

Table 2. Multidomain gait features for classification.

Domain	Features	Statistical Metrics
Temporal	Gait cycle duration, stance time, swing time, double support, cadence, step time	Mean, median, SD, coefficient of variation, IQR, symmetry index
Spatial	Step length, step width, stride length, step height, pelvic tilt, foot clearance	Mean, SD, symmetry ratio, RMS, max-min range
Frequency	Dominant frequency, harmonic ratio, spectral entropy, power spectral density (PSD), bandwidth	Peak frequency, spectral centroid, spectral flatness, energy ratio, entropy index

Technically, the combination of features from multiple domains has been shown to increase classification accuracy in previous gait analysis studies [5, 16].

The fusion of data from inertial sensors and RGB-D cameras also enhances the robustness of the analysis by enabling redundancy and cross-validation of the extracted features.

5 Expected and Preliminary Results

5.1 Expected Results

This experimental study aims to obtain a robust set of gait features that can accurately distinguish between normal and pathological patterns through multimodal analysis.

Structured Multimodal Database. A synchronized dataset containing accelerometry signals and RGB-D skeletal data for each participant, organized by gait type, healthy vs. pathological.

Feature Extraction and Validation. A set of temporal, spatial, and frequency-domain variables with discriminative power between different pathological groups is expected to be obtained.

Pathology-Specific Characteristic Profile. Group analysis will help identify which variables are most relevant for detecting specific pathologies such as Parkinson's disease, hemiplegia, or ataxia.

Experimental Design Efficiency. The proposed environment and protocol will be validated to ensure they enable the acquisition of high-quality, reproducible, and clinically meaningful data.

Preliminary Classification Model. Based on the extracted features, the initial development of a classifier such as SVM, Random Forest, or a lightweight neural network is anticipated, aiming to achieve high sensitivity and specificity in distinguishing between healthy individuals and those with gait impairments.

This set of results will lay the foundation for subsequent phases of the project, including clinical validation, sample size expansion, and the training of deep learning models.

5.2 Preliminary Results

Pilot tests have been conducted so far with five healthy subjects to evaluate the experimental setup and the multimodal data acquisition process. The following observations have been made:

Good synchronization between devices was achieved, successfully aligning the IMU signals (at 100 Hz) with the RGB-D camera data (at 30 fps) through the use of visual markers and shared features.

High fidelity in 3D skeleton reconstruction was verified, confirming the Kinect v2 camera's accuracy in joint tracking, which enabled stable calculation of joint lengths and angles.

Precise identification of gait events was accomplished through peak analysis in vertical acceleration and validation using heel joint displacement, allowing for accurate segmentation of gait cycles.

Consistency of key parameters such as step length (0.68 ± 0.05 m), cadence (110 ± 6 steps/min), and cycle duration (1.1 ± 0.1 s) matched the average values reported in the literature for healthy young adults [18].

Detection of inter-subject variability was observed, as small individual differences in pelvic motion amplitude and swing time were recorded, suggesting the system's sensitivity in capturing subtle features of gait patterns.

These initial findings validate the technical feasibility of the proposed experimental setup and support its application in populations with clinical gait impairments. As the sample size increases and subjects with specific pathologies are included, it is expected that distinct patterns in the extracted features will emerge.

6 Discussion

The preliminary results obtained in this experimental study support the feasibility of a multimodal approach for characterizing human gait, combining accelerometry signals and skeletal data from an RGB-D camera. This strategy has proven effective in identifying clinically relevant parameters in human gait, which is consistent with previous work in biomechanics and motion analysis.

The proper synchronization between inertial sensors and the Kinect camera has enabled accurate segmentation of gait cycles, which is essential for obtaining robust temporal variables such as the duration of stance and swing phases. This level of precision is crucial, as studies have shown that small variations in these parameters can indicate neurological conditions such as Parkinson's disease or peripheral neuropathies.

Likewise, the extracted spatial (e.g., step length) and frequency-based features (spectral components of movement) show interindividual differences that could serve as digital biomarkers in subjects with gait impairments. This perspective aligns with current trends in personalized medicine and clinical analysis using wearable technologies.

The methodological approach based on the Biodesign framework has allowed this study to be structured not only from a technical perspective but also with consideration of its future clinical applicability. This ensures that the proposed solutions are aligned with the real needs of hospital and rehabilitation settings, facilitating potential technological transfer.

Nevertheless, this study has limitations inherent to its early stage, such as the small number of participants and the lack of representation of various pathologies. As the sample size increases and participants with confirmed clinical diagnoses are introduced, the statistical and classification models developed are expected to be validated and refined. It will also be necessary to evaluate the system's generalizability in response to variations in the physical environment (e.g., surface type or lighting) and possible instrumental noise.

Finally, future phases of the project propose the integration of more sophisticated machine learning algorithms, including convolutional neural networks or hybrid architectures, to better exploit the temporal and spatial richness of the captured data.

7 Conclusions

This experimental study has demonstrated the technical and clinical feasibility of a multimodal design for extracting temporal, spatial, and frequency-based features in the gait of patients with motor impairments. The combination of accelerometers and RGB-D cameras enables a synergistic capture of data that enhances the quality and precision of biomechanical analysis, which is essential for the early detection and monitoring of gait disorders.

The preliminary results indicate that the proposed capture protocol is reproducible and suitable for obtaining synchronized and segmented signals, with parameters that align with specialized literature. This reinforces the applicability of the methodological framework based on Biodesign principles, which facilitates an effective integration between technological innovation and real clinical needs.

Among the limitations of the study are the small sample size and the need to include a greater diversity of pathologies to validate the generalizability of the extracted features. Additionally, the controlled environment of the experiment should be tested under more variable conditions to evaluate the robustness of the system.

In future stages, the extracted features will be processed using state-of-the-art multimodal classification algorithms. These may include support vector machines (SVM), random forests, convolutional neural networks (CNNs), and transformer-based models, which are capable of handling heterogeneous time-series and spatial data. The project has already included data from healthy individuals as well as patients diagnosed with gait-related conditions such as genu varum, genu valgum, knee osteoarthritis, and lumbar disc herniation, providing a representative foundation for training and evaluating the classifiers. These models are expected to support specialists in the diagnosis, progression tracking, and personalization of rehabilitation strategies through objective, non-invasive tools.

As future lines of research, the following are proposed:

– Expand the sample by including patients with specific clinical diagnoses to strengthen the comparative analysis and train predictive models using advanced machine learning [4].
– Implement longitudinal protocols to evaluate gait evolution in response to treatments or rehabilitation, identifying digital biomarkers of progress or deterioration.
– Integrate real-time analysis to provide immediate feedback to patients and therapists, facilitating personalized and adaptive interventions.
– Explore the incorporation of other sensory modalities, such as surface electromyography (sEMG) or plantar pressure sensors, to enrich the patient's biomechanical profile.

Together, this work constitutes a significant contribution towards the development of clinical monitoring systems that help improve the quality of life for individuals with motor impairments and facilitate clinical decision-making based on objective and quantifiable data.

References

1. Baker, R.: Gait analysis methods in rehabilitation. Clinics in Physical Therapy (2006)
2. Caldas, R., Mundt, M., Büttner, F., Kautz, T., Eskofier, B.M.: Wearable inertial sensors for human movement analysis: A review of posture and gait monitoring applications. IEEE Sensors Journal **17**(2), 394–405 (2017)
3. Del Din, E., Godfrey, C., Rochester, L.: Spatiotemporal gait analysis using a single wearable sensor in parkinson's disease. IEEE Transactions on Biomedical Engineering **63**(3), 699–707 (2016)
4. Esfahlani, F.Z., et al.: Deep learning for human gait analysis: A review. IEEE Transactions on Neural Systems and Rehabilitation Engineering **30**, 1501–1515 (2022)
5. Esfahlani, S., Luo, H., Yang, Z., Sarrafzadeh, M.: Deepgait: Temporal convolutional neural network for accurate gait phase detection in spinal cord injury. IEEE Journal of Biomedical and Health Informatics **25**(3), 732–742 (2021)
6. Espinosa, K., Alcaraz, G., Ramírez, R.: Gait event detection using inertial measurement units: a systematic review. Sensors **22**(3), 1–25 (2022)
7. Fida, B., et al.: Gait pattern classification using wearable inertial sensors. Journal of Biomechanics **48**(11), 3123–3129 (2015)
8. Gabel, G.G.: Introduction to Human Movement Analysis. Human Kinetics, Champaign, IL (2009)
9. Hausdorff, J.M.: Gait dynamics, fractals and falls: finding meaning in the stride-to-stride fluctuations of human walking. Human Movement Science **26**(4), 555–589 (2007)
10. Hermens, H.J., Freriks, B., Disselhorst-Klug, C., Rau, G.: Development of recommendations for semg sensors and sensor placement procedures. Journal of Electromyography and Kinesiology **10**(5), 361–374 (2000)
11. Muro-de-la Herran, A., Garcia-Zapirain, B., Mendez-Zorrilla, A.: Gait analysis methods: an overview of wearable and non-wearable systems, highlighting clinical applications. Sensors **14**(2), 3362–3394 (2014)

12. Silva de Lima, A.L., et al.: Wearable inertial sensors in clinical gait analysis: A systematic review. IEEE Reviews in Biomedical Engineering **13**, 248–263 (2020)
13. Mancini, M., Horak, F.B.: Quantifying postural stability using wearable sensors: a new approach to balance assessment. Physical Therapy **91**(12), 189–190 (2011)
14. Perry, J., Burnfield, J.M.: Gait Analysis: Normal and Pathological Function. SLACK Incorporated (2010)
15. Ranavolo, A., et al.: Instrumented gait analysis: An overview. European Journal of Physical and Rehabilitation Medicine **53**(4), 575–591 (2017)
16. Trojaniello, D., et al.: Comparative analysis of different methods for the estimation of temporal parameters of gait using wearable inertial sensors. Gait & Posture **42**(3), 360–365 (2015)
17. Wang, L., et al.: Gait recognition using wearable sensors. Sensors **17**(4), 825 (2017)
18. Whittle, M.W.: Gait Analysis: An Introduction. Butterworth-Heinemann, 5th edn. (2014)
19. Winter, D.A.: Biomechanics and Motor Control of Human Movement. Wiley, Hoboken, NJ, 4th edn. (2009)
20. Yock, P.G., Zenios, S., Makower, J., Brinton, T.J., Kumar, U., Watkins, T., Krummel, T.M.: Biodesign: The Process of Innovating Medical Technologies. Cambridge University Press (2015)